




The sspm R package: spatial surplus production models for the management of northern shrimp fisheries

Valentin Lucet ^{*1} and Eric J. Pedersen ^{†1,2}

¹ Department of Biology, Concordia University, Montreal, CA ² Department of Biology, Memorial University of Newfoundland, St. John's, CA

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

- [Review](#) 
- [Repository](#) 
- [Archive](#) 

Editor: [Open Journals](#) 

Reviewers:

- [@openjournals](#)

Submitted: 01 January 1970

Published: unpublished

License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#))

Statement of need

1. Population models, in particular fisheries productivity models, rarely integrate important spatially-structured ecosystem drivers
2. The Northern Shrimp stock in the Newfoundland and Labrador Shelves currently lacks a population model
3. Current SPM models are rarely spatially explicit and usually cannot account for relevant ecosystem drivers
4. Fisheries managers lack user-friendly, flexible tools to implement and apply SSPMs

Summary

Population modelling is an exercise of interest within environmental sciences and adjacent fields. Early population models such as the logistic model assumed that while the abundance of a population might change over time, the environmental conditions governing parameters affecting that rate of change (such as the maximum rate of growth or the carrying capacity of the population) stay constant over time ([Gotelli, 2008](#)). Modern population models increasingly acknowledge the non-stationary nature of wild populations, and work to incorporate environmental fluctuations into dynamic models ([Thorson et al., 2015, 2017](#)). Population models designed to answer applied resource management questions, such as fisheries stock models, increasingly address how the dynamics of stocks vary across space and time.

Resource managers are becoming increasingly interested in how variation in ecosystem factors such as predator abundance and abiotic variables impact the spatiotemporal variability of population parameters such as productivity ([Szuwalski & Hollowed, 2016](#); [Zhang et al., 2021](#)). Further, treating spatially structured stocks as single unstructured stocks can lead to substantially biased estimates of population change ([Thorson et al., 2015](#)). However, stock models that explicitly incorporate spatial dynamics and time-varying ecosystem variables still rare in fisheries science, despite the push for more ecosystem-based management methods in fisheries management ([Berkes, 2012](#); [Crowder et al., 2008](#); [Tam et al., 2017](#)).

Surplus production models (SPMs) are one of the classic models used in fisheries, and are based on modelling changes in the total biomass of a stock in a given location over time (i.e. *surplus production*) as a function of current stock abundance and fishing pressure ([Walters et al., 2008](#)). They are useful in data-poor contexts where the age and sex structure of the population is not accessible, or when age- or length-structure do not change substantially over time ([Prager, 1994](#); [Punt, 2003](#)). Classically, SPMs assumed single unstructured stocks with

*co-first author

†co-first author

39 purely logistic dynamics (Walters et al., 2008), and as such have been viewed as a limited tool
40 for modelling more complex stocks.

41 Two limitations of classic SPMs is the assumption of spatially constant productivity, and that
42 stock productivity is affected only by stock abundance and fishing. These assumptions ignore
43 the effect of global changes that are affecting fisheries, such as climate change, that affect
44 the growth rates of stocks independently of fishing pressure. One example is that of the
45 Northern Shrimp (*Pandalus borealis*) in the Newfoundland and Labrador Shelves, which has
46 undergone several periods of large-scale biomass change in the last two decades, despite a
47 relatively constant harvest regime (DFO, 2019). These stocks currently lack a population model
48 to understand the drivers of this change, and to predict how fishing pressure and changing
49 environmental conditions may affect future abundance in the region. In the context of climate
50 change and shifting ranges, fisheries productivity is likely to be a moving target (Karp et al.,
51 2019), and managers need better methods that account for varying productivity (Szuwalski &
52 Hollowed, 2016).

53 Population models like SPMs usually fall under two categories: process-based and statistical.
54 Process-based models often rely on differential or difference equations and are based on
55 replicating the underlying processes (e.g., predation, recruitment, dispersal) driving population
56 dynamics. Statistical models instead fit a regression model to time series of population
57 abundances, abundance indices, or productivities, with some assumed error distribution for
58 variation around predictions. This allows for estimation of parameter uncertainty and ranges
59 of model predictions, and for flexibly incorporating potential ecosystem drivers into models
60 (Plagányi et al., 2014). Statistical models also allow for straight-forward estimation of spatial
61 variation in population parameters such as maximum productivity or density dependence from
62 data, in the absence of theory predicting how these parameters should vary. In this paper,
63 we use a statistical approach to fitting SPMs using Generalized Additive Models (GAMS),
64 estimated using the mgcv R package (Wood, 2017) as the backend. We apply this approach
65 to the population of Northern Shrimp of the Newfoundland and Labrador Shelves, leveraging
66 the smoothing properties of GAMs to account for varying productivity across time and space.
67 The resulting model is a spatial SPM (SSPM), implemented via a R package *sspm*.

68 While the initial application of this model was modelling Newfoundland and Labrador Northern
69 Shrimp stocks (Pedersen et al., 2022), The R package *sspm* is designed to make spatially-
70 explicit surplus production models (SSPM) simpler to estimate and apply to any spatially
71 structured stock. The package uses GAMs to estimate spatiotemporally varying biomass,
72 and to estimate SSPMs based on changes in fitted biomass, observed catch, and spatially
73 structured environmental predictors. It includes a range of features to manage biomass and
74 harvest data. Those features are organized in a stepwise workflow, whose implementation is
75 described in more detail in Figure 1.

- 76 1. Discretization and aggregation of spatially structured observations into discrete patches,
77 with a range of methods of discretization (random or custom sampling, Voronoi tessella-
78 tion or Delaunay triangulation).
- 79 2. Spatiotemporal smoothing of biomass and environmental predictors using GAMs.
- 80 3. Computation of surplus productivity based on biomass density and fishing effort.
- 81 4. Fitting of SSPMs to productivity data with GAMs.
- 82 5. Visualization of results, including confidence and prediction intervals.
- 83 6. One-step-ahead prediction of biomass for model validation and scenario-based forecasting.

84 Although it was developed in a fisheries context, the package is suitable to model spatially-
85 structured population dynamics in general.

86 Package design

87 The package follows an object oriented design, making use of the S4 class systems. The
88 different classes in the package work together to produce a stepwise workflow (Figure 1).

89 The key workflow steps are:

- 90 1. Delineation of the boundary of the region of interest for the model. Boundary data
91 is provided as a shapefile and converted into a `sspm_boundary` object with a call to
92 `spm_as_boundary()`.
- 93 2. The region within the boundary is discretized into patches with the `spm_discretize()`
94 function, creating a `sspm_discrete_boundary` object.
- 95 3. The `spm_as_dataset()` function turns user-provided data frames of raw observations
96 into `sspm_dataset` objects that explicitly track locations, data types, and aggregation
97 scales for each input. `sspm` recognizes three types of data: **trawl** (i.e. biomass estimates
98 from scientific surveys), **predictors**, and **catch** (i.e. harvest).
- 99 4. The `spm_smooth` function use spatiotemporal GAM models to smooth the biomass and
100 predictor data, based on the spatial structure from `sspm_discrete_boundary`. The user
101 specifies a GAM formula with custom smooth terms. The output is another `sspm_dataset`
102 object with a `smoothed_data` slot which contains the smoothed predictions for all patches.
- 103 5. The `spm_aggregate_catch` function aggregates catch into patches and years, and calcu-
104 lates patch-specific productivity for each year as the ratio of estimated biomass density
105 plus catch from the next year, divided by estimated biomass density of the current year.
106 The result is returned as a `sspm_dataset`.
- 107 6. The `sspm` function combines productivity and predictor datasets into a single dataset.
108 Additionally, the user may create lagged versions of predictors with `spm_lag()` and split
109 data into testing and training sets for model validation with `spm_split()` at this stage.
- 110 7. The `spm()` function is used to fit a SSPM model to the output of step 6, using a GAM
111 model with custom syntax able to model a range of SSPMs. The output is an `sspm`
112 object.
- 113 8. Predictions from the fitted model can be obtained using the built-in `predict()` method,
114 and plots with the `plot()` method.

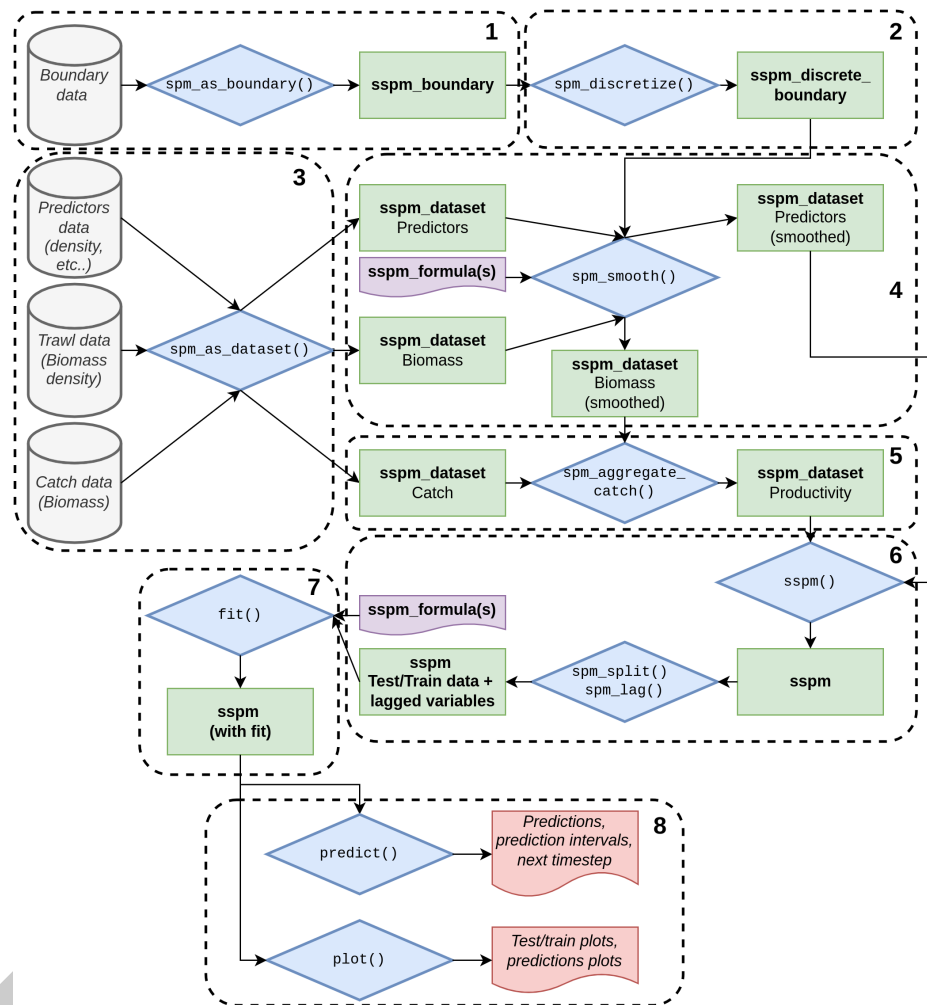


Figure 1: The sspm workflow.

Connections to other surplus-production based stock assessment approaches

The sspm package uses a model-based, random-effects based approach to estimate the effects of ecosystem drivers on surplus production across space and time. Our approach is conceptually related to the stochastic stock assessment approaches used by the R packages *spict* (Pedersen, 2017) and *jabba* (Winker, 2018). R packages for surplus production modelling, in that we assume that biomass dynamics can be modelled as effectively a logistic growth model with both process and measurement error. While sspm does not currently have the capacity to model biomass dynamics as a continuous-time process, as with *spict*, or incorporate prior parameter information on catchability or biomass dynamics as in *jabba*, sspm can model spatially and temporally varying productivity, which is currently not possible in these models.

The sspm package can be viewed as a spatiotemporal Model of Intermediate Complexity [a 'MICE-in-space' model; Thorson et al. (2019)] that can incorporate effects of other species and ecosystem drivers as well as changes in fishing pressure on stock status. Our approach is closely connected to approaches used by other modern model-based spatial abundance estimation software, such as the VAST R package (Thorson et al., 2019) and the sdmTMB R package (Anderson et al., 2022). Our method shares the same approach as both VAST and

sdmTMB of using spatially explicit models to estimate local biomass density (Figure 1 steps 1,2, and 4), then aggregating up from those models to predict aggregate stock-level metrics such as total biomass and productivity (Figure 1 steps 8). The multiplicative surplus production model used by sspm is also conceptually similar to the vector-autoregressive model for biomass changes used by these two packages, as both VAST and sdmTMB can model local temporal changes as autoregressive processes on the link-scale of a generalized linear model. The sspm package cannot, however, model the dynamics of multiple species simultaneously; multi-species modelling would require generating a separate surplus production model (Figure 1 steps 5 and 6) for each species of interest.

One major difference between the sspm package and other model-based spatiotemporal modelling packages is its special-purpose nature. The default spatial_smooth function uses a computationally simpler (although somewhat less flexible) Intrinsic Conditional Autoregressive (ICAR) model (Rue & Held, 2005) for modelling spatial variation in covariates and biomass, as compared to the more complex spatial random effects possible with VAST and sdmTMB. This has the advantage of computational speed and less user knowledge of how to set up complex spatial grids, although it is less flexible. This means that sspm should be easier to adapt to novel fisheries than more complex packages that require more user modelling knowledge. Further, it is possible to specify alternative spatial smoothers than the ICAR model in the spatial_smooth function via the bs= argument, although this functionality has not been well-tested and should be considered experimental.

The other benefit of sspm, relative to other modelling packages, is the ability to model productivity rates directly (Figure 1 steps 5 and 6), rather than implicitly via an auto-regressive processes as used in VAST or sdmTMB. This means that it is possible in sspm to model nonlinear relationships between environmental covariates and productivity, or to easily include factors such as time-lagged effects of predictors on productivity in a given year. This approach does, however, sacrifice the ability to propagate measurement error into uncertainty about rates of change. One of the future directions for development of this package is to include variance propagation methods into the surplus production modelling step.

Acknowledgements

This research was supported by the Canadian Department of Fisheries of Oceans (DFO) Sustainable fisheries Science Fund, and by a Discovery Grant from the Canadian Natural Sciences and Engineering Research Council (NSERC) to E.J.Pedersen. We thank Fonya Irvine and John-Philip Williams for their help in testing the package and providing feedback on model implementation.

References

- Anderson, S. C., Ward, E. J., English, P. A., & Barnett, L. A. K. (2022). *sdmTMB: An R package for fast, flexible, and user-friendly generalized linear mixed effects models with spatial and spatiotemporal random fields* (p. 2022.03.24.485545). bioRxiv. <https://doi.org/10.1101/2022.03.24.485545>
- Berkes, F. (2012). Implementing ecosystem-based management: Evolution or revolution? *Fish and Fisheries*, 13(4), 465–476. <https://doi.org/10.1111/j.1467-2979.2011.00452.x>
- Crowder, L. B., Hazen, E. L., Avissar, N., Bjorkland, R., Latanich, C., & Ogburn, M. B. (2008). The Impacts of Fisheries on Marine Ecosystems and the Transition to Ecosystem-Based Management. *Annual Review of Ecology, Evolution, and Systematics*, 39(1), 259–278. <https://doi.org/10.1146/annurev.ecolsys.39.110707.173406>
- DFO. (2019). *An assessment of Northern Shrimp (Pandalus borealis) in Shrimp Fishing Areas 4–6 and of Striped Shrimp (Pandalus montagui) in shrimp fishing area 4 in 2018* (Technical

- Report No. 2019/027; p. 23). Canadian Science Advisory Secretariat (CSAS).
- Gotelli, N. J. (2008). *A Primer of Ecology* (Fourth Edition). Oxford University Press. ISBN: 978-0-87893-318-1
- Karp, M. A., Peterson, J. O., Lynch, P. D., Griffis, R. B., Adams, C. F., Arnold, W. S., Barnett, L. A. K., deReynier, Y., DiCosimo, J., Fenske, K. H., Gaichas, S. K., Hollowed, A., Holsman, K., Karnauskas, M., Kobayashi, D., Leising, A., Manderson, J. P., McClure, M., Morrison, W. E., ... Link, J. S. (2019). Accounting for shifting distributions and changing productivity in the development of scientific advice for fishery management. *ICES Journal of Marine Science*, fsz048. <https://doi.org/10.1093/icesjms/fsz048>
- Pedersen, E. J., Skanes, K., Le Corre, N., Koen-Alonso, M., & Baker, K. (2022). *A new spatial ecosystem-based surplus production model for SFA 4-6 Northern Shrimp* (Can. {Sci}. {Advis}. {Sec}. {Res}. {Doc}. No. 2022/062; pp. 1–64). https://publications.gc.ca/collections/collection_2022/mpo-dfo/fs70-4/Fs70-4-2022-012-eng.pdf
- Plagányi, É. E., Punt, A. E., Hillary, R., Morello, E. B., Thébaud, O., Hutton, T., Pillans, R. D., Thorson, J. T., Fulton, E. A., Smith, A. D. M., Smith, F., Bayliss, P., Haywood, M., Lyne, V., & Rothlisberg, P. C. (2014). Multispecies fisheries management and conservation: Tactical applications using models of intermediate complexity. *Fish and Fisheries*, 15(1), 1–22. <https://doi.org/10.1111/j.1467-2979.2012.00488.x>
- Prager, M. H. (1994). *A suite of extensions to a nonequilibrium surplus-production*. 17.
- Punt, A. E. (2003). Extending production models to include process error in the population dynamics. *Canadian Journal of Fisheries and Aquatic Sciences*, 60(10), 1217–1228. <https://doi.org/10.1139/f03-105>
- Rue, H., & Held, L. (2005). *Gaussian Markov random fields: Theory and applications*. CRC press.
- Szuwalski, C. S., & Hollowed, A. B. (2016). Climate change and non-stationary population processes in fisheries management. *ICES Journal of Marine Science*, 73(5), 1297–1305. <https://doi.org/10.1093/icesjms/fsv229>
- Tam, J. C., Link, J. S., Rossberg, A. G., Rogers, S. I., Levin, P. S., Rochet, M.-J., Bundy, A., Belgrano, A., Libralato, S., Tomczak, M., Wolfshaar, K. van de, Pranovi, F., Gorokhova, E., Large, S. I., Niquil, N., Greenstreet, S. P. R., Druon, J.-N., Lesutiene, J., Johansen, M., ... Rindorf, A. (2017). Towards ecosystem-based management: Identifying operational food-web indicators for marine ecosystems. *ICES Journal of Marine Science*, 74(7), 2040–2052. <https://doi.org/10.1093/icesjms/fsw230>
- Thorson, J. T., Adams, G., & Holsman, K. (2019). Spatio-temporal models of intermediate complexity for ecosystem assessments: A new tool for spatial fisheries management. *Fish and Fisheries*, 20(6), 1083–1099. <https://doi.org/10.1111/faf.12398>
- Thorson, J. T., Jannot, J., & Somers, K. (2017). Using spatio-temporal models of population growth and movement to monitor overlap between human impacts and fish populations. *Journal of Applied Ecology*, 54(2), 577–587. <https://doi.org/10.1111/1365-2664.12664>
- Thorson, J. T., Skaug, H. J., Kristensen, K., Shelton, A. O., Ward, E. J., Harms, J. H., & Benante, J. A. (2015). The importance of spatial models for estimating the strength of density dependence. *Ecology*, 96(5), 1202–1212. <https://doi.org/10.1890/14-0739.1>
- Walters, C. J., Hilborn, R., & Christensen, V. (2008). Surplus production dynamics in declining and recovering fish populations. *Canadian Journal of Fisheries and Aquatic Sciences*, 65(11), 2536–2551. <https://doi.org/10.1139/F08-170>
- Wood, S. N. (2017). *Generalized Additive Models: An Introduction with R, 2nd Edition* (2nd ed.). CRC Press. ISBN: 978-1-4987-2837-9

- 227 Zhang, F., Reid, K. B., & Nudds, T. D. (2021). The longer the better? Trade-offs in
228 fisheries stock assessment in dynamic ecosystems. *Fish and Fisheries*, 22(4), 789–797.
229 <https://doi.org/10.1111/faf.12550>

DRAFT